EEG signal detection and analysis with application in educational robotics

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Abstract. Brain-Computer Interfaces add information to robots directly from users' brain, allowing for the interpretation of attention, engagement, and even student mistakes. However, most applications still have low accuracy in recognizing this information. In this paper, an Error Related Potential (ErrP) detection system is being proposed. For this, a new database was created by using a serious game and a humanoid robot aiming to force errors and mental state changings of the user. Wavelets and Fourier Transforms were compared to signal feature extraction, classified using both MultiLayer Perceptron (MLP) and Convolutional Neural Networks (CNN). Experiments demonstrate that the wavelet outperformed Fourier transform to extract the ErrP signal, and CNN had a higher accuracy than MLP in the classification.

Keywords: Brain Computer Interface, Biomedical Signals, Robotics

1 Introduction

Robotics can be used as a tool to offer opportunities and enhance engagement and high order thinking skills for students. Educational robotics was introduced in many schools as an innovative learning environment, helping students understand and solve complex real-world problems. Solve problems require a level of concentration, which varies according to difficulty, novelty, and tiredness. Further, these factors are the mental load that a task requires, which differs from mechanical tasks, *i. e.* of repetitive effort to tasks with cognitive loads, such as study and research. This concentration level also influences the errors made during each task, and the possibility of making mistakes tends to grow over time to solve the problem.

There are several methods for assessing the mental state and errors of subjects while performing a task. Body positioning, eye gaze, and yawning may be signs of tiredness or inattention, which increase the probability of mistakes [16]. In the educational character, intelligent schools have been proposed, which use sensors such as cameras and lasers to verify such information from students [10]. Another standard methodology is to enhance classes, using computers and robotics as an incentive, keeping students' attention for a more extended period and with satisfactory learning improvement results [3].

Another way to do this monitoring is by evaluating the user's brainwaves and interpreted by the machine through the technique known as Brain-Computer Interfaces (BCI). Brainwave signals can be acquired by an invasive, semi-invasive, or non-invasive method. Therefore, the non-invasive method eliminates the need for surgery and is the most recommended for research terms. Invasive procedures are used to treat diseases or recover from motor dysfunction when they need electrode implantation. The non-invasive method's disadvantage is the physical distance from the information's focus, giving sensitivity to many noises and artifacts externals to those to be investigated.

However, the algorithms' accuracy for filtering and classifying this signal is still low, and few studies have been developed for its use in the educational area. In this paper, the aim is to detect, filter, and classify participant's perception of mistakes during serious game sessions from brainwave signals. To this, a game was developed with PyGame to induce error and, consequently, the Error-Related Potentials (ErrP) in the brain. The detection of this behavior was done using the non-invasive method called electroencephalography. Since the signal provided by this technique is very noisy, filter algorithms have been compared, and the signal has been classified with different neural network models. The detection ErrP signal system proposed is part of a broader educational project ongoing. When applied to education, recognition of user errors can help in the system adaptation according to the student's performance during learning.

In this work, for ErrP detection and recognition, the techniques for feature extraction have been compared: Fast Fourier Transform (FFT), Wavelets, and Freeman K-Sets. For signal classification, some neural networks models, Multilayer Perceptrons (MLP) and Convolutional Neural Networks (CNN), have been used. We hypothesize that the wavelets transform will be able to extract better information from the EEG signal, and, when aligned with deep learning techniques, they will have better accuracy than demonstrated in the literature. The built database created behaves in the same way as previously available databases, but the experiment's control allowed a better extraction of characteristics and signal cleaning.

2 EEG Information

The brain's electrical activities result from nerve impulses emitted by the neurons, which indicates the action of the cerebral cortex [11]. The groups of neurons are excited during a nervous stimulus, for example, generating this activity, measured in the electroencephalogram (EEG), using electrodes positioned on the scalp. As it is a non-invasive technique, the signal is influenced by noise and artifacts, capturing information from populations of neurons. For this reason, the first challenge of a BCI system is the automatic interpretation of the EEG signal and the non-localized occurrence of the components.

The most common system to place the electrodes is the 10-20 system, proposed by Jasper *et. al.* [5], positioning to allow a more uniform coverage of the scalp. Figure 1 shows the positioning of the electrodes in this system, highlighting those used in this research. Sixteen electrodes placed in the Fpz, Fz, F8, FC3, FCz, FC4, C3, Cz, C4, CP3, P3, P4, P8, POz, O1, Oz positions, but for ErrP recognition, the most important are FCz and Cz. The letters indicate the lobe (**F**rontal, **P**arietal, **C**entral, **T**emporal and **O**ccipital). Even numbers represent right, odd left, and **z** center.

The captured signals are bandpass filtered for eliminating artifacts and cleaning the information. The zero-phase Butterworth IIR filter has set to reject signals above 0.5 Hz and below 100 Hz. Blink of eyes and heart beating was removed using ICA. The timing

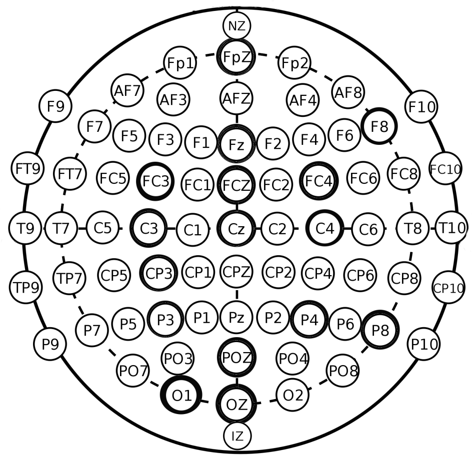

Fig. 1. International 10-20 position system [7].

of the likely appearance of ErrP was restricted in the database, as the game throws an external event whenever one of the zombie's abnormal behaviors happened. This signal marked the beginning and the end of the strange behavior, making it easier to cut out the epochs of interest to create the training set.

3 Methods

In this section, some preprocessing methods are presented, and some classification methods were chosen to detect ErrP signals.

3.1 Filter Algorithms

Mathematical transformations are applied to signals to obtain information that is not readily identifiable in the pure signal. Most of them are in the time domain, so the signal is measurable as a function of time. Usually, signals are represented by amplitude, generating a time-amplitude graph, but this is not always the best way to describe information. For biological signals, for example, symptoms and pathological conditions may be more evident in the frequency domain. There are many transforms to study: Hilbert Transform, Radon Transform, Wigner Distributions, among others. In this paper, the focus is on Fourier and Wavelet transforms.

Fourier Transform The well known Fourier Transform (FT) technique transforms the time domain signal to the frequency domain reversibly. That is, it is possible to return to the original signal. However, only one information is available at a time, or time or frequency. This feature is particularly important for the EEG because the signal is non-stationary. The technique consists of breaking down periodic signals into weighted sums of sine and cosine functions. However, due to the redundancy built into complex coefficients, the most widely used algorithm for signal processing is the Fast Fourier Transform.

Wavelet Transform Fourier Transform decomposes the signal into sines and cosines, i.e., the functions localized in Fourier space. In contrast, the wavelet transform uses functions that are localized in both the real and Fourier space. In 1909, Alfréd Haar published his Ph.D. thesis. Haar's paper introduced what was later recognized to be a fundamental wavelet system [13].

3.2 Classification

For comparison with neural networks, it was proposed to use an in-depth learning approach. These applications' main idea is sequential information, for example, video processing, language, or signals. For certain types of networks, as in Recurrent Neural Network (RNN), an output and an input are dependent, which have some implications for efficiency on many tasks. Newborns will get an answer, if necessary, a prediction, know the next sequence of action [9]. Thus, exploring deep architectures is their ability to learn how to process spatio-temporal information, which is essential in the EEG case.

The LSTM is a particular type of RNN network, capable of learning long-term dependencies. In some cases, it was necessary to have long term memory for the prediction. LSTM was created in 1997 [4], but its popularity has grown in recent years for different applications due to the good accuracy obtained.

LSTM is composed of a memory cell block and three multiplicative gates, called the input gate, output gate, inference, and forget gate. While the cells are responsible for maintaining information over long periods, the input gate is responsible for deciding what data to store. The output gate decides when to apply that information with the input and output gate units, respectively. Finally, the forget gate feeds the self–recurrent connection with its output activation. It is responsible for not allowing the cells' internal state values to grow without bound by resetting the internal states as long as it is needed.

CNN contains some main parameters called hyper-parameters. They are the filter Size, the kernel that can be 5x5, 7x7, etc. in the convolution layer, and the number of feature maps (the amount of K filters required in the convolution layer).

Convolution The human brain structure inspires convolutions. With each convolution function application, a region is changed, generating another example (called a feature map representing the original data). This data is changed using the kernel. In some situations, especially for imaging applications, this process can cause a lot of information loss, disrupting the network response, in which case the *padding* process is used, adding information before the convolution operation, seeking to maintain the dimensionality of the original data. The results of those convolutions generate representative features, enough to classify data. It is necessary to use learning algorithms to train kernel values.

4 Detection of ErrP signals

In Figure 2 is shown the process for detecting the ErrP signals. This proposed system is a module of a bigger project named R-CASTLE [15]. First, the signals (inputs) are received from the database built according to the explained process in section 2. The signals are then preprocessed using the zero-phase Butterworth IIR filter to reject signals above 0.5 Hz and below 100 Hz. The eyeblink was removed using a combination of Hilbert transform and an ICA enhanced with a wavelet transform, separated artifacts even with a lot of noise signal. The following filters were used to feature extraction: Daubechies, Haar (wavelet transforms), and FFT. Finally, the generated features vector is classified by using two different classifiers: MLP and CNN to be compared. The provided system output indicates if the signal input was or not an ErrP signal.

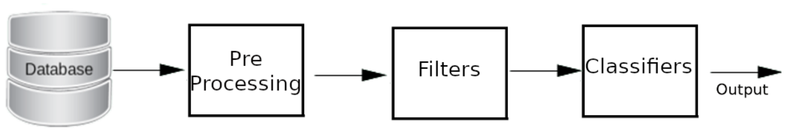

Fig. 2. ErrP Detection System

In the feature extraction phase, three methods were considered: 8 layers of Haar Wavelet [13], Fast Fourier Transform [2], and Daubechies wavelets from the pre-processed input data. This method is an improvement methodology that was used in [8], using one more wavelet transform. For both game and robot phases, the models are trained and evaluated using two sessions from a single subject, considering 80 windows, being half of each class.

4.1 Avaliation Metrics

For the classification, we choose the Resilient BackPropagation algorithm for Multilayer Perceptrons (MLP). The hyperbolic tangent was used as an activation function, fixed the number of hidden layers at 2, and varying the neurons' number in each layer. The results that will be shown corresponding to the best configuration found.

A second neural network, composed of a convolutional neural network (CNN) and LSTM (Long-Short-Term Memory) layers, as described in Table 1 trained with binary cross-entropy loss and Adam optimizer [6]. Figure 3 has presented the architecture, which is constituted by two convolutional networks, followed each one by 02 layers of ReLU and 01 fully connected network. MLP received the entire concatenated window as input, which does not faithfully represent the proposed problem, whereas the second model has the advantage of encoding the temporal information.

We used cross-validation to evaluate the classifier responses, a statistical method to estimate machine learning models' skill. It is commonly used in applied machine learning to compare and select a model for a given predictive modeling problem because

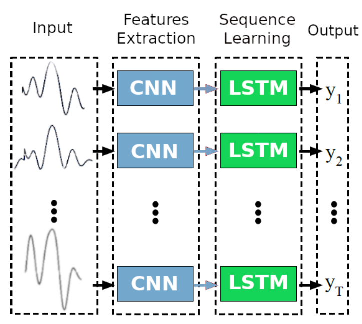

Fig. 3. Classification Process of signal pure EEG

Operation	Kernel Size	Output	Activation
Input	-	2048,2	-
Conv	100	2948,32	ReLu
MaxPooling	5	409,32	-
Conv	5	409,64	ReLu
MaxPooling	5	81,64	-
LSTM	-	100	Tanh
Dense	-	1	Sigmoid

Table 1. Architecture used in the experiments

results in skill estimate that generally have a lower bias. The k-fold Cross-validation method has the single parameter k that refers to the number of groups that a given data into the sample is split. The reported results correspond to the average of running 10-fold cross-validation three separate times with different random shuffling seeds.

5 Experiments: the game proposed

The creation of the database involved a game development in provoking three different types of ErrP events. For playing the game, the player must move a zombie to eat brains within 15 seconds. The goal is to eat most brains before time runs out. It is a relatively simple game, as no obstacle was placed in the calibration phase. Users must use the arrow keys to move the zombie, and no additional information about the game has been given. The idea was to understand the brain's behavior during the moments that there was no forced error by the game.

For the database's construction, eight healthy individuals were called to play the proposed game, five men and three women [1]. All individuals were volunteers to participate, were not informed of the experiment's objectives, had the same education level and knowledge of robotics and biomedical signs, and declared themselves well to do the experiment. The brain's behavior is related to age [14], so ages ranged from 20 to 34 years (M. = 25,75, S.D. = 5.192).

[1] Ethical Committee approval CAAE: 79649717.0.0000.5292

All participants were in an isolated room one-by-one, without noise or any other disturbance. Inside the room was only a computer, the robot, the subject, and the researcher, who gave all the instructions. The subject sat and wore the EEG cap, washed and sterilized with alcohol before each experiment. It was used the BrainProducts V-AMP, with 16 channels and only passive electrodes. To the game, two phases were created: one of calibration, when no error occurred, and another one of the tests, when the errors happened randomly. After the game, subjects are invited to interact with a humanoid robot, playing a quiz game. The following subsections describe all steps of this process.

5.1 Calibration

Users invited to the experiments were advised to wash their hair with shampoo but without any other products. Nor should they wear makeup, sunscreen, and creams on their head and ears. They were comfortably positioned in a chair, and they could use the computer and see the robot effortlessly. After helmet placement, the gel was applied to improve signal reading. This process can be seen in Figure 4.

Fig. 4. Game interface on real game phase

After applying the gel, the user should follow some commands to test the capture. Move eyes, blink repeatedly, move arms, among others. This quick procedure was done while the researcher followed the signal, checking the electrodes activated, ensuring that the sign was correct. Once this part was completed, the calibration phase was then started.

There were few differences between the two calibration rounds. Even though it was a simple game, not all users understood well in the first round of how the game worked, and everyone got better results in the second round. However, the most interesting difference is that the previous round score was now shown on the screen. The participant was warned that to continue playing, he had to beat his record of the prior round. Although subtle, the suggestion of having to be better to move on to the next phase adds some concern to the user, and it was necessary to understand brain-behavior in this condition.

5.2 Real Game

For the real game phase, the user should beat a previously defined high score to go to a supposed (and not real) stage 3. The game's interface had a black belt with three pieces of information: a clock in the center, points scored on the right and left round the score to beat. After 15 seconds, the game was programmed to generate three types of errors randomly:

- For 1 second, the zombie completely stops;
- For 2 seconds, the zombie saunters but respecting the directions imposed;
- For 2 seconds, the zombie moves randomly to a different side than indicated by the user. The zombie can behave differently each time this error occurs.

The player was not warned about the bugs in the game and the score, first easy to achieve, was unreachable due to these forced errors. Since there is no statistical difference in the types of errors that the user experiences [12], the different types of errors were created only to have slightly different ErrP waves for neural network training.

The researcher had no further interaction with the player, even if he complained about constant bugs. After the first flaw, the player was invited to try again, but knowing that the forced errors were part of the experiment. All the game elements were created to instigate the player and imitate situations that can happen to students in times of study and tests: desperation, the need to act quickly, and frustration. This information is essential to see the behavior of brain waves at all times of the game.

5.3 Robot Interaction

After the game over, users were invited to participate in the interaction session with a robot. Acting as naturally as possible (for a better acceptance by users [1]), the robot presented a quiz. A robot's choice for this experiment's stage is explained to increase the participants' level of attention by taking advantage of the novelty factor of an interaction with a humanoid robot.

The robot introduces itself as a new student and needs to know the participants' knowledge about two subjects: brain-behavior (simple group) and programming (complex group). Then, he explains that he will ask some questions and asks the user to answer them all, even if he is unsure of the answer. The student is asked to press the letter **k** (Know) or **u** (Unknown) on the keyboard. This interaction can be seen in Figure 5.

Fig. 5. Individuals participating in the experiment with the game and the robot.

The robot randomly asked six questions with different difficulty levels. There are three questions on a simple group, where participants were expected to find it more accessible and three programming questions beyond their knowledge scope. After asking the questions, the robot gave four alternative answers, which should be chosen by the participant.

During the interaction, the robot behaved in 3 different ways:

– **Behavior 1:** the robot hears the answer and acts as it was expected: says that it is right if the user's answer is correct and says that it is wrong if the user's response is wrong;
– **Behavior 2:** the robot hears the response and acts contrary to expectations: it says that it is right if the user's answer is wrong and says that it is wrong if the user's answer is correct;
– **Behavior 3:** the robot hears the answer, but it gets confused: if the user answers ”letter b,” the robot understands ”letter d.” In the group of easy questions, the robot always understood the wrong answer, and in the group of difficult questions, the robot always understood the right answer.

6 Results

As expected, the Wavelet transforms performed better than the Fourier transform, as shown in Table 2. Using all the information from the Haar transform and the Daubechies, the results, when ranked by MLP, were significantly better than using Fourier. The results are explained by the characteristic of analyzing the signal in time and frequency.

An interesting result was the low accuracy using only the last layer of the Haar transform. In the case of MLP its result was much lower than expected, close to FT's. Despite some good cases, on average, the final Haar result was bad.

Filter/ Classifier	True Positive	True Negative	Accuracy	Precision	Recall	F1 Score
db2/MLP	0.800	0.850	0.825	0.800	0.842	0.820
db2/CNN	0.900	0.900	0.900	0.900	0.900	0.900
db4/MLP	0.900	0.850	0.875	0.900	0.857	0.878
db4/CNN	0.925	1.000	**0.962**	0.920	**1.000**	**0.961**
Haar Complete/MLP	0.875	0.775	0.825	0.875	0.795	0.837
Haar Complete/CNN	0.875	0.975	0.925	0.875	0.972	0.921
Haar Final /MLP	0.825	0.700	0.761	0.825	0.733	0.776
Haar Final/CNN	0.925	0.975	0.950	**0.925**	0.973	0.948
FFT/MLP	0.725	0.675	0.700	0.725	0.690	0.707
FFT/CNN	0.775	0.720	0.750	0.775	0.738	0.756

Table 2. Comparing results using all extractors and classifiers

The use of CNN for classification, however, shows a significant improvement in some of the results. This conclusion is mainly due to mounting data for the classifiers. While MLP received a large feature vector, it is possible to divide the vector into parallel times for CNN. With this, the different channels' critical information became clearer to be extracted, helping enhance accuracy. As a disadvantage, CNN, especially for the classification of all 8 Haar layers, took a much longer time to finish. The time to classify and allow the system to respond, especially in interaction with the robot, was uncomfortable for social interaction.

In addition to accuracy, the means of precision, recall, and F1-score were analyzed. Accuracy represented the positives, that is, getting it right when ErrP occurred. The recall referred to the negatives, being the ability to hit when the signal was considered normal. In this analysis, it is interesting to note that Haar was better at precision, even for a very short percentage than DB4. Precision results are important because they represent finding the specific ErrP signal. For example, using Haar complete, even with accuracy with CNN increased, it still averaged the same number of ErrP signals, improving only normal pattern recognition.

Tests with another helmet indicated a significant decrease in the ability to recognize the ErrP of the proposed system, as shown in Table 3. The results in the table were obtained, considering 8 healthy children. It is worth remembering that tests corroborate all of these experiments on synthetic databases. Although it may mean that the system was unable to generalize the signal recognition, the hardware factor must be taken into account. The difference in the two devices' capture capacity is big, starting with a dry electrode and communication via Bluetooth, which inserts a noise into the signal. Software is available to clean signal with the headset, but much of what was applied in this work is lost, using a standard solution. Despite being likely results when compared to the literature, much of the solution presented is still lost.

Table 3. Bad results with other headset

Filter/Classifier	Accuracy
db2 / MLP	0.538
db2 / CNN	0.667
db4 / MLP	0.558
db4 / CNN	0.71
Haar Com / MLP	0.55
Haar Com / CNN	0.667
Haar Final / MLP	0.538
Haar Final / CNN	0.653
FFT / MLP	0.474
FFT / CNN	0.525

7 Conclusion

In recent works, it was noticed that one of the shortcomings in the robotic educational area is the treatment of the sensory information, the real time response, and the ability of the robots to adapt to the changing of the students' mental states. In this paper, it was proposed an ErrP detection system to fill these gaps. The pure EEG signal was preprocessed without the aid of other techniques. Feature extraction was then done using two classical techniques: Fourier and Wavelet transform, and the classification results were compared using different neural network models.

The results showed high accuracy in the classification using CNN, which is mainly because this kind of neural network considers the temporal information of the data. It is worth noting that the wavelet transform demonstrated a better performance in the signals' feature extraction. Moreover, the results showed a small accuracy difference among the classification using different wavelets, indicating that its simplicity and lower computational cost could choose the Haar wavelet. This choice is particularly important in real-time applications in which the speed of the system response to the user is vital for communication. The system was also able to generalize the small differences in the waveform error signal, enabling the robot to analyze the error in different mental states (nervousness, frustration, among others).

As future work, we intend to improve the robot using this system's feedback, turning it able to search for new content and change its behaviors based on the user reactions to given stimuli. The robot must adapt its behavior according to the student's measures of engagement, frustration, and errors. A smart search can be proposed, improving the automatic selection of the error moment, decreasing the manual service.

References

1. Breazeal, C.L.: Designing sociable robots. MIT press (2004)
2. Brigham, E.O., Brigham, E.O.: The fast Fourier transform and its applications, vol. 448. prentice Hall Englewood Cliffs, NJ (1988)
3. Edwards, A., Edwards, C., Spence, P.R., Harris, C., Gambino, A.: Robots in the classroom: Differences in students' perceptions of credibility and learning between "teacher as robot" and "robot as teacher". Computers in Human Behavior (2016)
4. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural computation **9**(8), 1735–1780 (1997)
5. Jasper, H.: Ten-twenty electrode system of the international federation. Electroenceph. Clin. Neurophysiol, 10:371-375 (1958)
6. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980 (2014)
7. Klem, G.H., Lüders, H.O., Jasper, H.H., Elger, C.: The ten-twenty electrode system of the international federation. the international federation of clinical neurophysiology. Electroencephalography and clinical neurophysiology. Supplement **52**, 3–6 (1999)
8. Pinto, A.H.M., Mijan, M.A.M., Nardari, G.V., Romero, R.A.F.: Comparing features extraction and classification methods to recognize errp signals. In: 2018 Latin American Robotic Symposium, 2018 Brazilian Symposium on Robotics (SBR) and 2018 Workshop on Robotics in Education (WRE). pp. 1–7 (Nov 2018)
9. Poormehdi Ghaemmaghami, M.: Tracking of humans in video stream using lstm recurrent neural network (2017)
10. Sanghvi, J., Castellano, G., Leite, I., Pereira, A., McOwan, P.W., Paiva, A.: Automatic analysis of affective postures and body motion to detect engagement with a game companion. In: Proceedings of the 6th international conference on Human-robot interaction. pp. 305–312. ACM (2011)
11. Sobotta, J.: Atlas da anatomia humana. 22. ed. Rio de Janeiro: Guanabara Koogan (2006)
12. Spüler, M., Niethammer, C.: Error-related potentials during continuous feedback: using eeg to detect errors of different type and severity. Frontiers in human neuroscience **9**, 155 (2015)
13. Stanković, R.S., Falkowski, B.J.: The haar wavelet transform: its status and achievements. Computers & Electrical Engineering **29**(1), 25–44 (2003)
14. Tatum, W.O.: Ellen r. grass lecture: Extraordinary eeg. The Neurodiagnostic Journal **54**(1), 3–21 (2014). https://doi.org/10.1080/21646821.2014.11079932, https://www.tandfonline.com/doi/abs/10.1080/21646821.2014.11079932
15. Tozadore, D., Pinto, A., Valentini, J., Camargo, M., Zavarizz, R., Rodrigues, V., Vedrameto, F., Romero, R.: Project r-castle: Robotic-cognitive adaptive system for teaching and learning. IEEE Transactions on Cognitive and Developmental Systems pp. 1–1 (2019). https://doi.org/10.1109/TCDS.2019.2941079
16. Yasui, Y.: A brainwave signal measurement and data processing technique for daily life applications. Journal of physiological anthropology **28**(3), 145–150 (2009)